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A TOPSIS based cluster head selection for wireless sensor network

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Abstract

The energy consumption is one of the most common issues in the Wireless Sensor Networks (WSNs). Since the communication usually accounts as a major power consumption, there are some techniques, such as topology control, to decrease the activity of the sensor's transceivers. Clustering is a topology control mechanism that selects some Cluster Head (CH) to manage the entire network. In this paper, we use a multi-criteria decision-making method for selecting CH with regard to the four criteria: the residual energy, the number of neighbors, the distance below the base station and the transmission range for each node. This method by taking various criteria of nodes causes that the best node be selected as the CH. This choice toward the previous algorithms, reduces the overhead associated with the CH. This method uses technique for Order Preference by Similarity to Ideal Solution (TOPSIS) in two levels, which caused the best value for each node in the WSN is selected. This method causes that the CH selection be done with higher accuracy, and the network lifetime increase significantly compared to the previous methods. Finally, the proposed method is compared with Analytical Hierarchy Process (AHP) and Low-Energy Adaptive Cluster Hierarchy (LEACH); the obtained results of repeating of this method show that this method increases the lifetime.

Keywords: Wireless sensor networks; Clustering; Multi-criteria decision-making method

1. Introduction

One of the major limitations of WSNs is the energy source in the nodes. So often, various techniques such as clustering algorithms are employed and the sensors are clustered into a group. This grouping is done in a manner

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that, some of the nodes on the network select as a CH and other nodes as members of the cluster[1]. Clustering in the WSNs is necessary and there are plenty of reach works for it[2].

In the most of the researches, residual energy[3] or number of neighbors or combination of them is considered as criteria for selecting CHs[3]. In the best knowledge of authors, except in[4] that Yin et al. proposed a CH selection algorithm that utilizes AHP, the most researches in CH selection consider one or two parameters. This algorithm increased network lifetime significantly, but this method has been overhead because of sending messages to all nodes. In other words, among the methods that have been proposed for clustering of WSN so far, Multi-Criteria Decision-Making (MCDM) methods have rarely been attended. There are several other classes of MCDM which can be termed as Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM)[5]. MADM methods have been widely used to solve a variety of uncertainty problems. MADM models are capable of selecting the best alternative out of a given list of alternatives based on their prioritized attributes[6].

In this paper regarded the CH selection problem as a MADM problem and a method has been suggested that in addition to using several criteria for CH selection, it uses the optimal number of clusters for clustering and compared with the previous algorithms, increases the lifetime of the network. This method reduces the overhead due to CH selection by selection of the optimal number of CH.

The layouts of the paper are as follows. Section 2 presents an overview of related work. The system model as well as the problem statement and proposed algorithm are mentioned in Section 3 and in the last Section 4 evaluates the simulation of the proposed method. At the end, raised the conclusion, some problems and future works.

2. Related Work

Decision making is always an important issue in all scientific fields. Nowadays, utilizing interdisciplinary methods increases. Utilize solving methods of MCDM models have used in various disciplines to find a better alternative than other available alternatives. For example, in[7] a case of using multi-criteria decision for analysis of medical images has been seen. So far, numerous methods for clustering WSNs are proposed that some of them are noted in[8-13]. Also, heuristic methods for clustering are used in these networks, for example, we can mention[14, 15]. Presented clustering algorithms are often divided into two categories: static and dynamic. In static approaches, CH is not changed during the period of clustering. These methods have been described in[16-18].

However, in the dynamic ways similar to proposed method, CH nodes periodically are changed. Amongst the dynamic clustering methods, it can be mentioned to Energy Efficient Clustering Scheme (EECS)[19] that is a multi-criteria approach that for selection the CH it uses three criteria: residual energy, the distance between CH nodes and the distance between the CH and the base station. This method wasted energy by sending a message to all nodes. This method has been amended by Multi-criterion Optimization technique for Energy efficient Cluster formation in wireless Sensor networks (MOESC)[20] that only offers a multi-criteria optimization to form clusters. Algorithm Energy Efficient Unequal Clustering (EEUC), this method is similar to EECS algorithm. In addition, each node needs to global information such as location and distance of the node's sink. The algorithm tries to prolong the life of the network and balance loads between nodes. This algorithm solves the excited position problem. Cluster size is proportional to the distance of the base station. But the integration of additional data adds the overhead sensor nodes, especially for multi-hop sensor networks[21]. Another method is Hybrid Energy-Efficient Distributed clustering algorithm (HEED). It uses two criteria, the amount of residual energy and number of neighbors to choose the CH. Although this method uses more parameters to CH selection compared to the previous methods, but this method does not guarantee the optimal number of clusters[22]. Communication cost within the cluster in this protocol referred to the degree's node or nodes near the neighbor. This parameter is used to connect to the cluster. Unlike LEACH, this protocol does not use a random method to select CH. Only nodes with higher residual energy are selected as CH and other algorithms are: Adaptive and Energy Efficient Clustering algorithm for content based wireless sensor networks (AEEC)[23], and Partition-based LEACH algorithm for wireless sensor networks (PLEACH)[24].

Another clustering method that is the nearest approach to our work is AHP. This algorithm based on AHP[4] is a centralized scheme for the selected CH based on MADM. Factors affecting the lifetime of the network include: the residual energy, the mobility and the distance to the base station. At each stage, CHs are selected based on mobility and node's energy remaining. In this way, it is proved that the lifetime of the network, increased significantly.

However, among these methods, LEACH algorithm presented as the first clustering algorithm and other algorithms use this algorithm as a basis of the algorithm[25].

In[26], Khalily et al. stated a theoretical determination of the achievable maximum multi-cast-information flow for various topology control mechanisms. Their simulation results demonstrated topology control mechanisms decrease both energy consumption and maximum-information flow. Note, maximum multi-cast-information-flow can be obtained by network coding approach. Khalily et al. proposed a joint optimal design of topology control and network coding in[27]. They formulated the problem of topology control in network-coding-based-multi-cast WSN with the delay and reliability constraints as a non-convex-mixed-integer-nonlinear-optimization problem that was named OTRA. For obtaining an optimal solution of OTRA, there is no polynomial-time algorithm and it is NP-hard problem.

3. Proposed algorithm by TOPSIS

Number of optimal cluster is calculated by a relationship. It continues with a density of nodes, and while the nodes begin to die once and smaller, clusters are combined with larger clusters. Base station is the node that collects data from all CH and has no limitation on energy. A simple dissipation radio energy model[28] to transmit a message with k bits, by a distance d, has been used to reach an acceptable ratio of signal to noise. Consumed energy for transmission is given by following equation[6].

$$E_{TX} = k * E_{elec} + k * \varepsilon_{fs} * d^2 \text{ If } d \le d_0 \tag{1}$$

$$E_{TX} = k * E_{elec} + k * \varepsilon_{mp} * d^4 \text{ If } d \ge d_0 \tag{2}$$

where E_{elec} is the energy dissipated per bit to run the transmitter or receiver circuit and ε_{mp} , ε_{fs} are the consumed energy in the amplifier and depends on the amplifier model and $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$. Consumed energy of time of final reception is as followed.

$$E_{RX} = k * E_{elec} \tag{3}$$

In every period, decision making is very important for the number of clusters that are in the region for maximizing energy efficiency. Every cluster has a CH that collects received data from cluster members, but this node does not do part of sensing operation. Number of optimal cluster is calculated by a relationship that is depend on density of nodes, and while the nodes begin to die once and smaller, clusters are combined with larger clusters. The optimal number of the cluster for each period is calculated by the following equation[29].

$$K_{opt} = \sqrt{\frac{\varepsilon_{fs}}{\pi\left(\varepsilon_{mp} d_{toBS}^4 - E_{elec}\right)}}.M\sqrt{N} \tag{4}$$

Although the number of CHs is given by the optimal solution, but the number of CHs in each period are not fixed. CHs are ranked by TOPSIS method and a number of CHs with higher rank, are selected for clustering.

Initially, each node, sends its local information such as the amount of residual energy and its distance from the base station to the base station and base station processes the information received from all nodes and places them in separated records, and stores with the status of being the dead or alive node. A node dies while lost their energy after some transmission period. In addition to this information, the number of neighbors of each node that selected according to the selected transmission range by TOPSIS are estimated and stored by the base station.

Table 1. Decision matrix for transmission range selection.

Alternative	The transmission range	The number of neighbour	The transmission power	Average energy consumption
1	15	8	225	0.0002
2	20	12	400	0.000275
3	50	30	2500	0.000285
4	70	57	4900	0.0002

Consider hundreds of sensors deployed in a 100*100 square meter area. Here it is assumed that the base station has no limitation in terms of energy, and the coordinates of (50,175) are placed. Size of sent packets is 500 bytes and size of exchange packets is 25 bytes. We first form a decision matrix for transmission range selection of every node by taking three parameters as mention in table 1. Then form a decision matrix for sensors to select the best CH, by taking four criteria. These value in table 1 and 2 are according to area network.

Table 2. Decision matrix in second round for CH selection.

No. node	The number of neighbour	The residual energy	Distance to the base station	The transmission range
1	57	0.4995	90.0965	70
2	27	0.4998	91.6012	50
3	14	0.4999	165.7752	20
4	12	0.4994	122.3339	20
5	39	0.4999	90.8687	70
6	26	0.4999	85.1296	50

Then, normalized matrix is calculated according to TOPSIS as followed. In this part, decision matrix is normal by using Euclidean norm.

$$n_{i,j} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m} r_{ij}^{2}}} \tag{5}$$

Where $n_{i,j}$ indicates the normalized value of alternative i in terms of criterion j.

Table 3. Normalized decision matrix by TOPSIS.

No. node	The number of neighbor	The residual energy	Distance to the base station	The transmission range
1	0.12905	0.079014	0.061663	0.0007507
2	0.061129	0.079062	0.062693	0.0005351
3	0.031697	0.079078	0.11346	0.0002146
4	0.027169	0.078988	0.083727	0.0002146
5	0.088298	0.079078	0.062191	0.0007507
6	0.058865	0.079078	0.058264	0.0005351

Then weighted matrix is calculated by the following equation.

$$V = N \times W_{n\times n} \tag{6}$$

In this equation, N indicated without scale matrix and $W_{n\times n}$ is the diagonal matrix of weights.

Table 4. Normalized decision matrix in second level.

No. node	The number of neighbour	The residual energy	Distance to the base station	The transmission range
1	0.032263	0.079014	0.014207	0.0045834
2	0.015282	0.079062	0.014444	0.0032739
3	0.0079242	0.079078	0.026141	0.0013095
4	0.0067921	0.078998	0.019291	0.0013095
5	0.022074	0.79078	0.014329	0.0045834
6	0.014716	0.079078	0.134240	0.0032739

Then positive ideal solution and negative ideal solution are calculated as follows.

$$v^+ = \left[\left(Max\left(v_{i,j}\right), j \in j_1\right), \left(Min\left(v_{i,j}\right), j \in j_2\right), i = 1,2,3,\ldots,m\right] \tag{7}$$

$$v^- = \left[\left(Min\left(v_{i,j}\right), j \in j_1\right), \left(Max\left(v_{i,j}\right), j \in j_2\right), i = 1,2,3,\ldots,m\right] \tag{8}$$

Where, j_1 corresponds to benefit criteria and j_2 corresponds to cost criteria.

Table 5. Positive and negative ideal solution.

v^+	0.12905	0.15816	0.10892	0.045834
v^-	0.013584	0.158	0.055054	0.0098216

Then distance of each alternative with positive and negative ideal solution is calculated.

$$d_i^+ = \sqrt{\sum_{j=1}^{m}\left(v_{ij} - v_j^-\right)^2}\ , d_i^- = \sqrt{\sum_{j=1}^{m}\left(v_{ij} - v_j^+\right)^2} \tag{9}$$

At the end, the closeness ratio of every alternative is calculated as followed. Thus all the CHs are ranked in descending order of $CL_i^* = \dfrac{d_i^-}{d_i^- + d_i^+}$.

Table 6. Result of ranking by TOPSIS.

No. node	d^+	d^-	CL^*
1	0.049724	0.12102	0.70879
2	0.084616	0.053029	0.38526
3	0.10271	0.056923	0.35659
4	0.11075	0.028922	0.20707
5	0.063898	0.08307	0.56522
6	0.088911	0.050758	0.36342

According to the scores that have been obtained for each alternative by using TOPSIS method, the results of ranking are as followed.

Table 7. Ranking by TOPSIS.

No .node	6	5	4	3	2	1
Rank	4	2	6	5	3	1

As regard to accomplish ranking, in the next step, we select the nodes with higher rank as CH in the optimal number.

After determination of the CHs, the CHs send an advertisement message over the network to announce their presence as CH of the network. Now each node measures its distance from selected CHs. Nodes attach to the CH that has the shortest distance from it and sends a message to the nearest CH. If the distance between nodes and CH is further from distance from the base station, this node directly communicates with the base station, otherwise connects to the cluster with nearest Euclidian distance. As a result, clusters are formed in this way. Nodes are re-clustering based on distance from the selected CH. CH allocated a time interval to each member's node after receiving all CH connection messages from all nodes. Each CH is an agent who receiving data from all the members. When a CH received a data frame from all members, after integration of the data sends them to the base station. When other group members can go into sleep mode at any time, the CH must be remained in active mode. Operation of re-clustering and data transfer for a period will continue until all the nodes die. If the cluster size is smaller than the predefined threshold, the cluster integrates to neighbor cluster. After nodes die, it is understood that a small number of nodes are present in the cluster. So with reduction of the number of alive nodes in each period, the number of clusters and the amount of information despite the remaining nodes in the physical area are reduced.

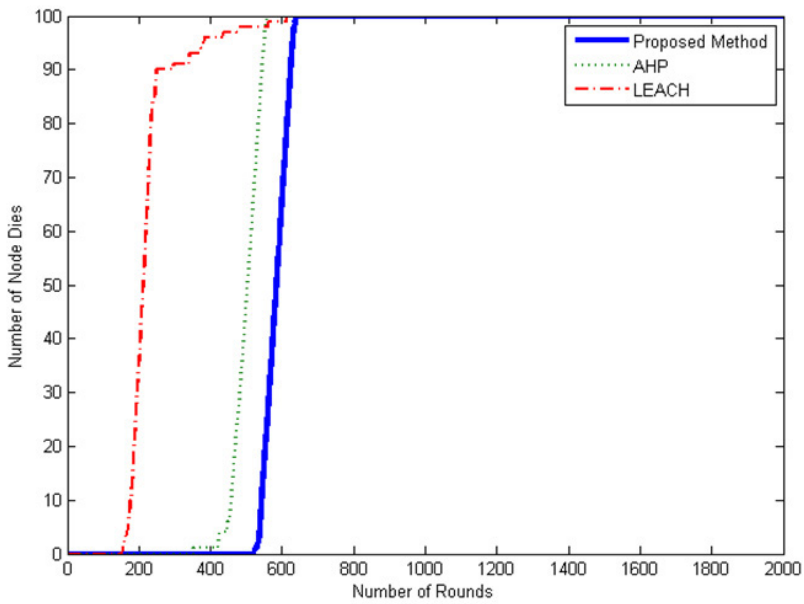

Fig. 1. Network Lifetime.

4. Simulation Result

The simulation has been accomplished in MATLAB software. A network model similar to[28] has been used. Table 8 shows the simulation parameters for experiments. Each period consists of clustering and data transfer phase. In this table, N is the symbol of the number of nodes, and EO is the initial energy of nodes.

Fig. 1 show improvement network lifetime of the proposed method compare with AHP and LEACH. This is due to that increase the parameters in selection CH increased accuracy for selection CH and reduced energy consumption of the sensor nodes. Moreover, long life of the CHs helps the sensor nodes to be more active.

Table 8. Simulation parameter.

Symbol	Value
N	100
ε_{fs}	$10pj / bit / m^2$
ε_{mp}	$0.0013pj / bit / m^4$
E_o	$0.5j$
E_{elec}	$50nj / bit$

5. Conclusion

This paper proposed a method for clustering by utilizing TOPSIS for CH selection in WSNs. This algorithm by finding best node as CH, improved network lifetime. The proposed method specifies the optimal number of CHs. We considered four criteria in CH selection, the number of neighbors, the residual energy, distance to the base station and the transmission range. The simulation results showed that the proposed algorithm improved network lifetime compare to LEACH and AHP. For future works, with adding the number of criteria for each node, network lifetime improves without adding high cost for the network. Also in accomplished studies, combination of the available methods that has presented for solving multi-criteria decision making, by taking into account the different states for a decision matrix; may be improve the lifetime.

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